

Enhancing Manufacturing-Quality-Performance indices by Automatic manufacturing-measurement process in Conventional machining

Sushil V. Deshpande^{1,2*}, Ramkisan S. Pawar³, Ashok J. Keche⁴, Sachin S Yadav⁵

^{1,4}Department of Mechanical Engineering, Maharashtra Institute of Technology, Aurangabad - 431010, Maharashtra, India

²Department of Mechanical Engineering Dr.D Y Patil Institute of Technology, Pimpri, Pune, 411018, Maharashtra, India

³Department of Mechanical Engineering, Padmabhooshan Vasantdada Patil Institute of Technology, Pune 411021, Maharashtra, India

⁴Genba Sopanrao Moze College of Engineering, Balewadi, Pune- 411 045, Maharashtra, India

*Corresponding Author: deshpande.sushilv@gmail.com

ABSTRACT

In traditional manufacturing procedures, accurate dimensional specifications are essential for producing high-quality items. However, manually evaluating and optimizing these factors may be time intensive and error-prone. This research presents a simultaneous automated assessment and optimization method to improve product quality during conventional production procedures. By combining sophisticated sensor technology with real-time feedback mechanisms, the suggested system continually analyses dimensional parameters and provides operators with rapid assistance, reducing mistakes and increasing process efficiency. This technique, using a holistic approach, greatly improves product quality, decreases cycle time and increases overall productivity in traditional production environments.

Keywords: process parameters, instantaneous feedback control, dimensional closeness, process elimination, cycle time.

INTRODUCTION

In today's ever-evolving manufacturing landscape, where precision and excellence are non-negotiable, ensuring the accuracy of work pieces during production is paramount. However, this essential task of inspecting work pieces can inadvertently lead to operator fatigue, especially in the realm of general-purpose turning. Understanding the distinct challenges and risks associated with inspecting work pieces in this context is essential for maintaining both productivity and the well-being of operators. This paper delves into the phenomenon of operator fatigue that arises from inspecting work pieces during general-purpose turning in manufacturing processes. It scrutinizes the specific factors contributing to fatigue, explores their potential impacts on operators and production efficiency, and presents strategies to alleviate fatigue-related issues. By shedding light on these challenges and proposing solutions, this research aims to enhance both the performance and the working conditions within machining processes. In the manufacturing industry, turning processes are commonly employed to create precise and intricate parts such as stepped shafts.

Gokcen Basa et.al describes Machining advancements which focus on both the final product's quality and its visual appeal (surface finish). This research proposes a detailed measuring plan to assess the machine tool's condition throughout the machining process (before, during, and after) to ensure cutting accuracy. High-precision measurement techniques are used to realistically evaluate the system's performance and ensure it meets international quality standards for geometric product specifications. Various measurement methods, including both physical contact and non-contact techniques, will be explored in the next section. This paper explains various contact and non-contact techniques for after manufacturing product inspection and does not focuses on going measurement. [1]

Oleksik M et.al develop, manufacture, and operate a tool with optimal functional geometry, allowing for a decrease in the dynamic phenomena that occur during the cutting process. To conduct the investigation, the front turning with transversal advance cutting procedure was used. Semi-finished items with a diameter of $\varnothing = 150$ mm manufactured of C45 steel were selected for processing (1.0503). The production operations were carried out using two tools: a cutting

tool, the traditional construction version, and another, the upgraded construction version. This paper focuses on geometrical references of tool only. [2]

Yi-Tsung Lin et.al introduces rough machining of scrolls, adaptive feed rate planning was utilized to compute the cutting area per cutter tooth in real time, allowing the feed rate to be adjusted and the material removal rate (MRR) optimized under a certain maximum tolerable cutting load. To eliminate noise in the semi-fine and fine machining operations, chatter frequencies were detected with a microphone, and spindle speeds were quickly adjusted using a designed programmed in conjunction with the milling machine controller. Using the Taguchi approach and analysis of variance (ANOVA), we identified the optimal milling settings for fine machining procedures to enhance contour features such as profile errors and scroll surface roughness. [3] Factors like Capacity utilization

Machine downtime rate, Operator relief are not ensured.

Katrin Ullrich et.al more comprehensive approach that considers multiple goals at once. The paper reviews existing research on using artificial intelligence (AI) and optimization techniques to improve machining of various types (milling, turning, etc.). Interestingly, milling and deep learning are the most common technique combination studied. While surface roughness is the most analyzed quality measure, the paper argues for a broader approach that considers all important aspects of machining. Finally, the paper identifies key factors for achieving significant improvements in overall machining performance.[4] This paper do not emphasize on problem of operator to be handled and efforts reduction. Paper focuses less on operator ease of manufacturing and measurement simultaneously.

To overcome the issues related to cycle time, complex and frequent measurement of dimension, utilization of sources, integrated automated measurement system with a lathe's control system allows for real-time adjustments during machining, along with alarms for out-of-tolerance conditions. This combined data collection and analysis not only improves quality control and reduces errors, but also offers valuable insights for further process optimization.

METHODOLOGY

The Smart Setup creates a precise workflow for monitoring work piece measurements throughout the machining process. The precision deployment of two laser line distance sensors is at the heart of the system. A lateral sensor positioned on the tailstock must be exactly aligned with the center of the work piece for accurate diameter measurement. In addition, a longitudinal sensor is mounted on a specialized holder and intersects the work piece axis laterally to measure length. Sliding attachments offer the flexibility required to fine-tune sensor placements and obtain ideal measurement circumstances.

Once the sensors are correctly positioned, data collecting and processing begin. The sensors link to a Raspberry Pi via an Analog-to-Digital converter (ADC), which converts analogue sensor signals into digital data that the computer can comprehend. This data is then passed into the built algorithm, which runs on a separate laptop. The magic happens thanks to a dual-display setup. [6] One display has a portion dedicated to dimensions, which shows a box that continually changes with both the standard measurement and the real-time measured value. This enables fast comparison and identification of any differences. The second display shows a live view of the work piece, emphasizing finished areas and the current region being machined. To improve visualization, a color coding scheme might be applied to indicate dimensional changes, giving operators a simple method to track progress and possible difficulties.

Evaluation of Manufacturing, Quality and Performance indices

3.1 Manufacturing indices includes on-time completion tracks how well a manufacturer meets client deadlines, a more comprehensive picture of production health is achieved by incorporating additional metrics.[5] Manufacturing indices, like cycle time (average time to complete a unit), capacity utilization (percentage of available production time used), and machine downtime rate (percentage of time machines are not operational), provide valuable insights.[10-12] These, along with overtime rate (amount of extra time worked) and Manufacturing Quality Indices (defect rates and rework needs), offer a holistic view of the production process. Analyzing these indices helps identify bottlenecks, optimize resource allocation, and ultimately achieve greater efficiency and profitability. [7-8]

3.1.1 Manufacturing Metrics

How do you measure manufacturing efficiency? Lean manufacturing KPIs are metrics that examine and help you improve process efficiency. Use lean KPIs to identify opportunities where you can reduce waste and increase speed.

Cycle Time

How long, on average, does it take to complete a customer order? Cycle time helps you understand how prepared your business is to meet customer demand.

Cycle time = (Time of start of actual manufacturing – Time of end of actual manufacturing)

Capacity Utilization

Capacity utilization measures how much of a plant's production capacity is in use. Look to this KPI to assess efficiency and future growth.

Capacity utilization = (Total capacity used during specific timeframe / total available production capacity) X 100.

Machine Downtime Rate

Machine downtime is how long equipment is unavailable to manufacture products. Machine downtime includes planned and unplanned downtime for scheduled maintenance for equipment failure.

Machine manufacturing downtime rate = Total uptime / total uptime + total downtime[

3.1.2 Quality indices

First Pass Yield

First pass yield (FPY) measures a line's output and quality performance. FPY is computed by dividing the number of "good" units that depart a process without requiring rework or scrapping by the number of units that enter the same process over a certain time period.

First Pass Yield (FPY) = Quality Units/Total Units Produced

Scrap Rate

Here scrap is defined as the ration of number of work pieces rejected to the total number of work piece manufactured

Rejected Piece / Total Piece produced = Scrap rate

Defect Rate

Simplify your quality management efforts with Tulip

Error-proof production steps, increase the efficiency and frequency of quality checks and ensure only high-quality materials and parts moves downstream.

3.1.3 Performance indices

How do you determine production KPIs? Manufacturing performance or production metrics measure the success of each stage of manufacturing.

Production Achievement

Output attainment assesses manufacturing's ability to fulfil goal output levels. The greater the score, the more effective the performance

Production attainment = (actual production/scheduled production) x 100.

Changeover Time

Average Interruption time per piece in min = Total time of interruption (j) in min / the number of change overs (k) in min [12-14]

4. Observations of manufacturing indices

Observation done for n=20 Job pieces during actual manufacturing of Job.

Table 01 Compares Manufacturing indices of two different machining methods

Sr No.	Manufacturing indices							
		1	2			3		
	Actual Mfg Time in min	Cycle Time (start time – End time) Per piece in min	Total capacity used during specific time frame (A)	Total available production capacity (B)	Capacity Loading A/B*100	M/C Run Time per piece *n min (A)= Total run time	M/C down time per piece*n =Total M/C down time (B)	Total M/C Mfg Down time Rate A/(A+B)
General Method of	19	27	2	2	100%	380	8*20(w/p)= 80	70

machining								
Machining with automatic measurement	17	19	1.5	2	75%	340	2*20=40	94

This table compares manufacturing performance for two different machining methods. It includes several key metrics:
 Cycle Time: This is the average time it takes to complete a single unit, measured in minutes (Sr. No. 1). Capacity Utilization: It represents the percentage of total available production capacity that is actually being used (Sr. No. 3). It's calculated by dividing the total capacity used (A) by the total available capacity (B) and multiplying by 100. Machine Run Time: This shows the total run time of the machine per unit produced, considering a specific number of units (n) (Sr. No. 4). It's obtained by multiplying the machine run time per piece by n. Machine Downtime: Similar to run time, this metric reflects the total downtime experienced by the machine per unit produced (n) (Sr. No. 5). It's calculated by multiplying the machine downtime per piece by n. Machine Manufacturing Downtime Rate: This ratio indicates the portion of total production time where the machine is not functioning due to downtime (Sr. No. 6). It's calculated by dividing the total machine downtime (B) by the sum of total run time (A) and downtime (B).

The table compares two scenarios:

General Method of Machining (Sr. No. 1-3): This method has a cycle time of 19 minutes per piece and utilizes 100% of the available capacity. The machine run time per piece is 380 minutes, resulting in significant downtime of 70 minutes per piece. Machining with Automatic Measurement (Sr. No. 4-6): This method boasts a faster cycle time of 17 minutes per piece and utilizes 75% of the capacity. While the machine run time per piece is lower at 340 minutes, the downtime is drastically reduced to only 20 minutes per piece. This translates to a lower machine manufacturing downtime rate compared to the general method. Overall, the table suggests that machining with automatic measurement offers a more efficient process with faster cycle times and reduced downtime, even though it utilizes less of the total capacity.

Table 02. Compares Quality indices of two different machining methods

Sr No	Quality Units (c)	Total Units Produced (d)	% First Pass Yield c/d*100	Rejected Piece (e)	Total Piece produced (f)	Scrap rate e/f*100	No of pieces with defect occurred (Not rejected) (g)	defect rate g/10*100
	General Method of machining	16	20	80	3	15	20	11
Machining with automatic measurement	20	20	100	Nil	20	0	4	20

The table compares quality results between two different machining methods using several key metrics:

Quality Units (c): This represents the number of units that meet quality standards (Sr. No. 1, 2). Total Units Produced (d): This is the total number of units produced, including both good and rejected units (Sr. No. 1, 2). First Pass Yield (%): This metric indicates the percentage of units that meet quality standards without requiring rework or rejection (Sr. No. 3). It's calculated by dividing the number of quality units (c) by the total units produced (d) and multiplying by 100. Rejected Piece (e): This reflects the number of units that failed to meet quality standards and were rejected (Sr. No. 5). Scrap Rate: This is the percentage of rejected units out of the total number of units produced (Sr. No. 7). It's calculated by dividing the number of rejected pieces (e) by the total units produced (d) and multiplying by 100. Defect Rate: This metric captures the overall percentage of units that have defects, including both rejected and non-rejected units with defects (Sr. No. 9). It's calculated by dividing the number of pieces with defects (not rejected) (g) by the total number of units produced (d) and multiplying by 100.

The table compares two scenarios:

General Method of Machining (Sr. No. 1-4): This method achieved a first pass yield of 80%, with 3 out of 20 units rejected. This translates to a 15% scrap rate. Additionally, 11 units had defects but were not rejected, resulting in a total

defect rate of 55%. Machining with Automatic Measurement (Sr. No. 5-8): This method achieved a significant improvement in quality. It produced 20 units with a 100% first pass yield, meaning zero rejects and a 0% scrap rate. However, 4 units still had defects but were not rejected, leading to a 20% overall defect rate.

Overall, machining with automatic measurement demonstrates a clear advantage in quality control. It achieves a significantly higher first pass yield, eliminates rejects, and reduces the scrap rate to zero. However, there's still room for improvement in reducing the overall defect rate.

Table 03. Compares performance indices of two different machining methods

Sr No	Performance indices					
	Actual production (h)	Scheduled production (i)	Production attainment $h/i*100$	total time of interruption (j) in min	the number of change overs (k) in min	Average Interruption time per piece in min (j/k)
General Method of machining	20	23	86%	8	4	2
Machining with automatic measurement	22	23	95%	2	1	0.5

The table examines the performance efficiency of two machining methods through several key metrics:

Production Attainment: This reflects the percentage of planned production that was actually achieved (Sr. No. 3). It's calculated by dividing actual production (h) by scheduled production (i) and multiplying by 100. **Interruptions:** This category captures the total time (j) and number of occurrences (k) of interruptions that occurred during production (Sr. No. 4, 5). **Average Interruption Time per Piece:** This metric indicates the average amount of time per unit produced that was lost due to interruptions (Sr. No. 6). It's calculated by dividing the total interruption time (j) by the number of changeovers (k). The table compares two scenarios:

General Method of Machining (Sr. No. 1-4): This method achieved 86% production attainment, falling short of the scheduled production target. It experienced a total of 8 minutes of interruptions across 4 changeovers, resulting in an average interruption time of 2 minutes per unit produced. **Machining with Automatic Measurement (Sr. No. 5-7):** This method demonstrates a significant improvement in production efficiency. It achieved 95% production attainment, coming closer to meeting the scheduled output. Additionally, it experienced fewer interruptions, with only 2 minutes of downtime across 1 changeover. This translates to a much lower average interruption time of just 0.5 minutes per unit produced. Overall, machining with automatic measurement offers a clear advantage in terms of production efficiency. It achieves a higher production attainment and experiences significantly less downtime due to interruptions. This suggests a more streamlined and reliable production process.

CONCLUSION

Data suggests Machining with automatic measurement is a more efficient method due to its faster cycle time (19 minutes vs. 27 minutes), lower machine downtime per piece (2 minutes vs. 8 minutes), and consequently lower overall downtime rate, despite slightly lower capacity utilization (75% vs. 100%).

In General Method of Machining the factors like are with First Pass Yield: 80%, Scrap Rate: 15%, Defect Rate: 55%. This method has a relatively low first pass yield, resulting in rework or rejection of a significant portion of produced units. The high scrap rate indicates a need for stricter quality control measures. The additional defect rate suggests that even units that pass inspection might have some quality issues.

In Machining with Automatic Measurement the factors like are with First Pass Yield: 100%, Scrap Rate: 0%, Defect Rate: 20%. This method achieves a significant improvement in quality control. It eliminates rejects and reduces the scrap rate to zero. However, there are still defects present in some units that pass inspection, highlighting the need for further process refinement to reduce the overall defect rate.

While the General Method achieved higher scheduled production attainment (86%), Machining with automatic measurement demonstrates superior overall efficiency. This is evident from its higher actual production (22 hours), significantly lower interruption time per piece (0.5 minutes), and fewer changeovers, suggesting a smoother and more productive operation.

REFERENCES

- [1]. Assessment of the Production Quality in Machining by Integrating a System of High Precision Measurement Gokcen Basa , Lachezar Stoevb , Numan M. Durakbasa, DAAAM 2014, Procedia Engineering 100 (2015) 1616 – 1624, doi: 10.1016/j.proeng.2015.01.535
- [2]. Oleksik M, Dobrotá D, Tomescu M, Petrescu V. Improving the Performance of Steel Machining Processes through Cutting by Vibration Control. Materials (Basel). 2021 Sep 30;14(19):5712. doi: 10.3390/ma14195712. PMID: 34640112; PMCID: PMC8510501.
- [3]. A Study on Improving the Machining Performance of Scrolls, Yi-Tsung Lin, Jia-Lun Jhang, Michael Schabacker, Der-Min Tsay, Guan-Shong Hwang and Bor-Jeng Lin, Published: 26 December 2022, 13(1), 286; <https://doi.org/10.3390/app13010286>,
- [4]. Katrin Ullrich, Magnus von Elling, Kevin Gutzeit, Martin Dix, Matthias Weigold, Jan C. Aurich, Rafael Wertheim, I.S. Jawahir, Hassan Ghadbeigi, AI-based optimization of total machining performance: A review, CIRP Journal of Manufacturing Science and Technology, Volume 50, 2024, <https://doi.org/10.1016/j.cirpj.2024.01.012>.
- [5]. Daniel Gauder, Johannes Götz, Niels Jung, Gisela Lanza, Development of an adaptive quality control loop in micro-production using machine learning, analytical gear simulation, and inline focus variation metrology for zero defect manufacturing, Computers in Industry, Volume 144, 2023, 103799, ISSN 0166-3615, <https://doi.org/10.1016/j.compind.2022.103799>.
- [6]. Sachin S. Kamble, Angappa Gunasekaran, Abhijeet Ghadge, Rakesh Raut, A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs- A review and empirical investigation, International Journal of Production Economics, Volume 229, 2020, 107853, ISSN 0925-5273, <https://doi.org/10.1016/j.ijpe.2020.107853>.
- [7]. Paul Kengfai Wan, Torbjørn Langedahl Leirimo. Human-centric zero-defect manufacturing: State-of-the-art review, perspectives, and challenges, SINTEF Manufacturing AS, Grøndalsvegen 2, 2830 Raufoss, Norway Available online 17 October 2022 0166-3615/© 2022
- [8]. Evaluation of performance in manufacturing organization through productivity and quality, Syed Irshad Ali1, *, Jamil Yousof, Memmona Rauf Khan, and Syed Ather Masood, Vol. 5(6), pp. 2211-2219, 18 March, 2011, Available online at ISSN 1993-8233 ©2011 Academic Journals, DOI: 10.5897/AJBM10.720
- [9]. Li, X.-Q.; Wang, Z.; Fu, L.-H. A Laser-Based Measuring System for Online Quality Control of Car Engine, Block. Sensors 2016, 16, 1877. <https://doi.org/10.3390/s16111877>
- [10]. E. Strömstedt, O. Svensson, and M. Leijon, A Set-Up of 7 Laser Triangulation Sensors and a Draw-Wire Sensor for Measuring Relative Displacement of a Piston Rod Mechanical Lead-Through Transmission in an Offshore Wave Energy Converter on the Ocean Floor, 05 Mar 2012, Volume 2012, Article ID 746865 | <https://doi.org/10.5402/2012/746865>
- [11]. Hirak Dipak Ghael, Dr. L Solanki, Gaurav Sahu, A Review Paper on Raspberry Pi and it's Applications, 06 01-2021, Volume 2, Issue 12, 225-227, IJAEM, DOI: 10.35629/5252-0212225227 ,
- [12]. Shiraishi, M., Sumiya, H., and Aoshima, S. (June 17, 2005). In-Process Diameter Measurement of Turned Work piece With Curvatures by Using Sensor Positioning, ASME. J. Manuf. Sci. Eng. February 2006; 128(1): 188–193. <https://doi.org/10.1115/1.2122967>
- [13]. Vrochidis Alexandros, Charalampous Paschalis, Dimitriou Nikolaos, Kladovasilakis Nikolaos, Chatzakis Michael, Georgiadis Giorgos, Tzovaras Dimitrios, Krinidis Stelios, Automatic elevator shaft inspection using a multi-sensor measuring system and computer vision techniques, Journal of Building Engineering, 2024, Volume 82, 108358, <https://doi.org/10.1016/j.job.2023.108358> .
- [14]. Dawei Ding, Wenfeng Ding, Rui Huang, Yucan Fu, Fengyu Xu, Research progress of laser triangulation on-machine measurement technology for complex surface: A review, Measurement, Volume 216, 2023, 113001, <https://doi.org/10.1016/j.measurement.2023.113001>.